Review of Quality Engineering Technologies in the Context of Industry 4.0

Thesis

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Abstract

Quality engineering is arguably in crisis. The search phrase "quality engineering" has been trending downward for over a decade and traditional methods such as lean six sigma are garnering reduced interest. This review seeks to reinvigorate quality engineering by studying Quality 4.0, i.e., quality for smart manufacturing. Following questions are addressed: (i) What is Quality 4.0? (ii) What are its impacts on operational performance? (ii) What roles can quality researchers usefully play in relationship to Industry 4.0 and IIOT? The results suggest a growing consensus that the body of knowledge for quality engineers is rapidly changing to emphasize most notably machine learning. Another conclusion is that the topics identified by ASQ in the body of knowledge are relatively unexplored by research authors. These include methods to shift attention from variation reduction in operators to automatic process design for quality, the monitoring and design of self-managing machines, and an increased emphasis on methods for big data analytics. Also, topics relating to dashboards and software for IIOT such as PTC Thingworx, Siemens Mindsphere, and Power BI are conspicuously absent.

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Chapter 1. Introduction

1.1 Literature Review

Previous research has proposed the concept of Quality 4.0 and identified some related quality engineering techniques that align with emerging capabilities of Industry 4.0. A recent review of Industry 4.0 for smart manufacturing and the Industrial Internet of Things (IIOT) has identified opportunities for quality engineering techniques to be applied and possibly extended in part by focusing on sensor integration[1]. Other research has inspired some calls for major reforms of the quality engineering discipline in response to Industry 4.0[2]. In fact, ASQ has an extensive new body of knowledge related to Quality 4.0[3]. This new body of knowledge was apparently inspired in part by articles in *Quality Progress*[4-5]

1.2 Significance of Research

Industry 4.0 is the ongoing transformation of manufacturing and industrial practices using modern “smart” technology[6]. This term is associated with radically higher levels of product customization, flexible manufacturing, and information transparency supported by interconnected machines, cloud computing, and big data analyses[7]. The Industry 4.0 market for software and services is expected to reach $156.6B by 2024 world-wide[8].

The phrase “Industry 4.0” is widely reported as originating in 2011 from a project sponsored by the German government and was publicly introduced in the same year at the Hannover Fair. At the same time, Google searches indicate interest in this term since 2004 (see Figure 1). In addition to the growth in interest in Industry 4.0, Figure 1 also provides perspective on the generally declining interest in “quality engineering”. This decline, noted in Zonnenshain and Kenett[2], motivates the need to reimagine quality engineering and promote “Quality 4.0.” Figure 1 also suggests that popular interest in the portion of Industry 4.0 relating to quality engineering, i.e., Quality 4.0, is (still) limited in the public consciousness.

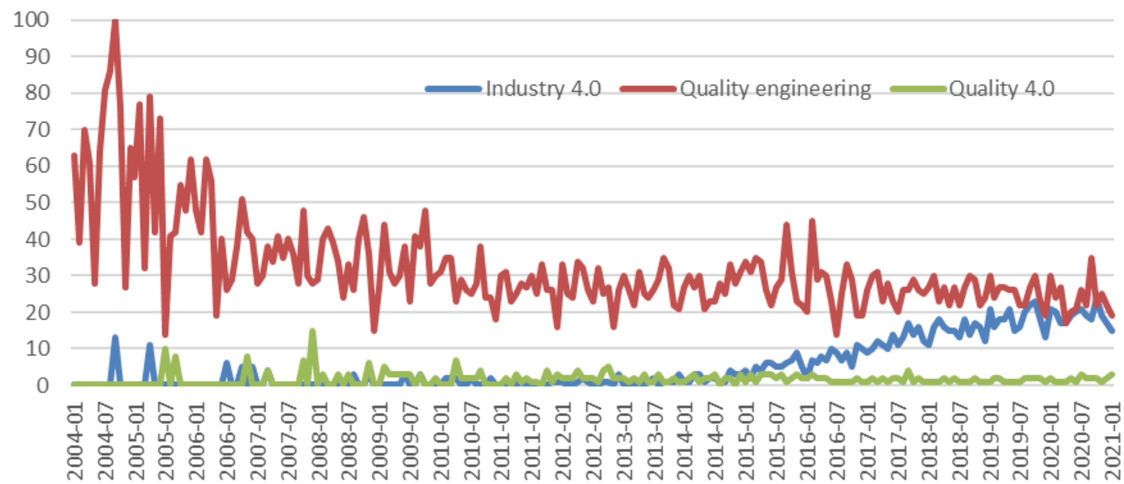

Figure 1 Google trends analysis of search interest

1.3 Overview of Thesis

The thesis has four chapters. In Chapter 2, Quality 4.0 will be defined building on the definitions in Zonnenshain and Kenett and from the ASQ body of knowledge[3]. Then the methodology used to select and classify the articles will be detailed. The taxonomy is itself a synthesis of the terms used in Zonnenshain and Kenett[2] and Radziwill[4]. Chapter 3 includes analysis of statistical trends in the literature relating to research interest and authorship. Also included in the analysis are many articles on Quality 4.0 relating to specific methods and search terms and relates Quality 4.0 to the broader literature on quality engineering. In Chapter 3, the literature regarding the impacts of Quality 4.0 on company performance is summarized. Chapter 4 concludes with a synthesis of the literature and a discussion of areas for future research.

Chapter 2. Methodology

2.1 Defining Quality 4.0

Zonnenshain & Kennet review the increasingly accepted history of industrial revolutions. To simplify, the first industrial revolution occurred roughly between 1760 and 1820 and related to by-hand production transitioning to machine-based production. The second revolution saw the advent of electrification and mass production between 1871 and 1914. The third revolution related to mass customization and computers in the 1980s and 1990s. The industrial internet of things and big data is being characterized by some analysts as the fourth industrial revolution.

While it is not entirely clear whether the fourth revolution should be viewed as a continuation of the third revolution, standard quality concepts and techniques, e.g., Shewart charting, relate closely to the second industrial revolution. This is evident when we study how ASQ defines the Certified Quality Engineer who:

> "...understands the principles of product and service quality evaluation and control...and statistical methods to diagnose and correct improper quality control practices, an understanding of human factors..."

There is little emphasis on statistical methods in the definition. Also, there is no mention of artificial intelligence and its branch, machine learning, big data, or the Internet of Things. This disconnect and the generally mature nature of quality engineering have triggered a concern in the quality literature. For example, Zairi (2017)[9] argues that quality engineering is "in crisis" and needs new "DNA" related primarily to the "the digital revolution for proactive pursuit of excellence.”

Also, Zonnenshain & Ron S. Kenett effectively define Quality 4.0 engineering in terms of developing an “appreciation for variation” in the context of sensors and big data analytics. Further, the definition of Quality 4.0 tools from ASQ implies a radical reimagining of the field. The old body of knowledge from the ASQ website is on the left-hand-side above the internal border of Table 1 and the new Quality 4.0 body of knowledge is on the right above the internal border. Items below the internal border in Table 1 will be further addressed in the conclusion section of this article (Section 7). Note also that ASQ acknowledges that AI includes machine learning, e.g., so that not all the tools in the table have the same scope.

From inspection of Table 1, it seems that ASQ (at least) sees Quality 4.0 as radically different from traditional quality engineering. The Quality 4.0 engineer is apparently an expert on artificial intelligence, IIOT, and block chain. Further, this new type of engineering does not need to know much of the previous body of knowledge about quality including soft skills such as quality management, assurance, and human factors engineering.

Table 1. The ASQ listed tools for (a) quality engineering (above the line) and (b) Quality 4.0 (above the internal line). The items below the internal line relate to proposals made here.

(a)	(b)
Quality Tools	Quality 4.0 Tools
Cause-and-effect diagram	Artificial intelligence
Check sheet	Big data
Control chart	Blockchain
Histogram	Deep learning
Pareto chart	Enabling technologies
Scatter diagram	Machine learning
Stratification	Data science
Design of Experiments	Virtual & Augmented Reality
	Spatial Analyses & RFIDs
	Dashboarding & Human Factors
	Digital Twins

With such a radical seeming transformation, it might seem that either academics or practitioners or both are getting carried away. Vining et al. (2015) warned us that the pressures on faculty cause us to seek “sexy” new techniques such as AI methods for the sake of funding. This can cause a gap between practitioners and faculty.

Yet, two things seem clear. First, there really is industry interest in AI and IIOT relating to quality improvement. Practitioners really do want experts to bring deep learning and other advanced modeling techniques into environments previously related primarily to response surface polynomial models and Kriging metamodeling. Second, the old quality engineering body of knowledge is surprisingly relevant to the practice of real-world AI.

With these new realities in mind, Quality 4.0 engineer can be defined:

> "…understands the principles of product and service quality and statistical and selected machine learning methods to diagnose and correct improper quality control practices. The engineer also has a familiarity with the human factors design of IIOT dashboards and related data collection and machine learning-based analyses."

This definition seems to offer a compromise between rejecting the still valuable traditional quality engineering body of knowledge and accepting needed reforms.

2.2 Literature search and selection

To reveal the trend and requirements of Quality 4.0, the study started by defining relevant keywords listed in Table 2, which were classified into two groups: Industry 4.0-related and quality-related. To reveal general trends and requirements of future quality engineering, the search starts from Industry 4.0 and then spreads to derivative concepts in the context of Industry 4.0. Advanced by Industry 4.0 technologies, manufacturing processes have transitioned to a more intelligent state, which is often described by terms such as Cyber-Physical Manufacturing, smart manufacturing, cloud manufacturing, and digital manufacturing. Those new modes of manufacturing are usually interconnected or featured by key technologies, such as the Internet of Things (IOT), Industrial Internet of Things (IIOT), cloud computing, and big data analytics.

Some papers also discuss traditional quality techniques (control charting, design of experiments, reliability modeling…) and how they can be adapted to the industry 4.0 environment, which offers another effective way to search relevant articles. The intersection of quality engineering and Industry 4.0 technologies is still recent; therefore, Google Scholar were mainly used to find more relevant articles. Besides, combinations of those keywords were also searched in Scopus to check the general trend and number of publications within a specific category. The websites of some publishers were also searched, including Taylor and Francis Online, and Wiley Online Library. Papers selected through the search: (1) were published between 2015 and January 2021; (2) include at least one of the keywords listed in Table 2 in either the title, abstract or keywords. The search is then refined by reviewing the contents to ensure that it is relevant to the topic. Papers that mention only one or several of the terms without further discussion were eliminated. Finally, 66 articles were selected. Journals that contribute at least one article are listed in Table 3.

Table 2. Keywords used to search articles.

Industry 4.0 related		Quality-related
Fourth industrial revolution	Digital manufacturing	Quality
Smart manufacturing	Cyber-physical manufacturing (CPS)	Six sigma
Internet of Things (IOT)	Cloud	Statistical Process Control (SPC)
Industrial Internet of Things (IIOT)	Big data	

Table 3. List of journals or proceedings with at least one article in this study

Quality Engineering
Quality and Reliability Engineering International
Production & Manufacturing Research
Journal of Quality Technology
Journal of Manufacturing Systems
International Journal of Production Research
IISE Transactions

2.3 The classification strategy

The papers were classified using the six descriptors listed in Table 4. Authorship types are divided into three categories; the authors either come from academic institutions (A), industrial companies (I), or mixed (AI). Industrial sectors are divided into manufacturing

(M) services (S), or general (G). Journal impact factors are based on data from the Science Citation Index (SCI).

Adapted from Zain et al.[10], papers are classified into the following categories: theoretical with application, case studies, survey results, literature review, or other. This classification is based on the research approach. Following categories in Yet et al.[1], papers are also divided by topics of application: IOT-based cloud manufacturing, supply chain and logistics, cyber-physical manufacturing, operations management, safety and ergonomics and general or other. Yang et al.[1] also mentioned energy efficiency management as a separate topic, which is included in the "general or other" category in this review since few articles focus solely on energy saving.

Table 4. Criteria used for classification.

Descriptor	Source	Levels and Ranges
Authorship	Allen	Industrial(I), Academic(A), or Both (I & A written IA)
Impact Factor	SCI	1.635 to 6.495
Research Approach	Zain et al.	Theoretical with Application (TA), Literature Review(R), Case study (Ca), Survey (Su), Comparative (Co)
IOT Manufacturing Applications	Yang et al.	IOT-Based Cloud Manufacturing(I), Cyber-Physical Manufacturing (CPS), Operations Management (OM), Supply Chain and Logistics (SC), Energy Efficiency Management (Em), Safety and Ergonomics (SE)
Industry Sector	Zain et al.	Manufacturing(M), Services(S), General or Other(G)

Chapter 3. Results

3.1 Literature Review

3.1.1 Literature Trends

Figure 2 plots the number of articles published in the database each year. The clear implication of the chart is that Quality 4.0 is attracting increasing interest. In fact, it is plausible to conclude that the number of related publications is growing exponentially. Figure 3 sheds light on which journals are playing key roles in publishing Quality 4.0 related research. Interestingly the two top journals--the *International Journal of Production Research* (Taylor & Francis) and the *Journal of Manufacturing Systems*--are not published by ASQ. This suggests that the ASQ professional society's change in body of knowledge commitments is not being mirrored in its associate research community. This might represent an opportunity for additional involvements.

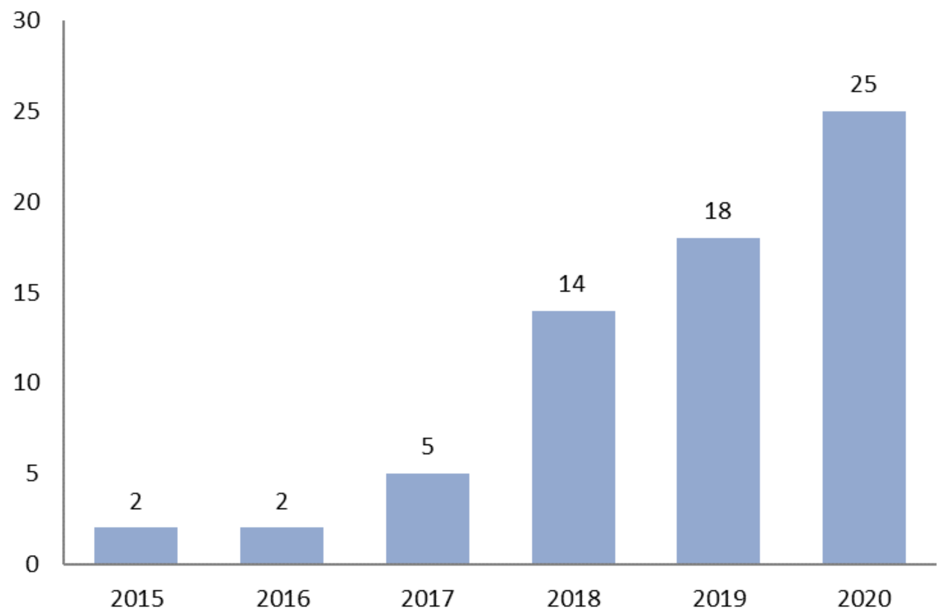

Figure 2 Number of articles over time. Papers are published before January 2021

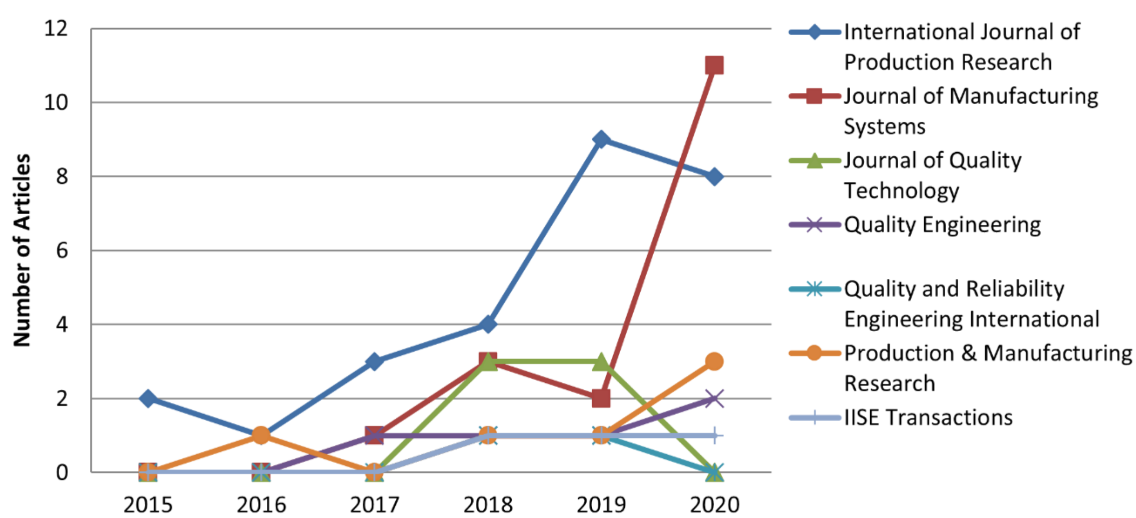

Figure 3 Number of Articles by source

3.1.2 Research Approach and Authorships

Figure 4 shows the yearly number of articles by types of author (Industry, Academic, or both). In the database of articles, nearly 87% of publications are written by academic authors. This is surprising as, like lean six sigma, Quality 4.0 originated in manufacturing and was developed first by industrial personnel. Yet, lean six sigma authors have included a relatively large proportion of practitioners[11]. This might relate to the relatively technical nature of Quality 4.0, with its emphasis on machine learning. As shown in Figure 4, more industrial authors are beginning to generate publications in recent years. Perhaps, this might indicate that the work is becoming more practical and less complicated. As noted in Figure 5, the industrial authors tend to focus on journals with lower citation rates (impact factors). Also, the publications in more highly cited journals have related to the service sector somewhat more than other areas. Figure 7 supports the view that the publications are generally theoretical in nature with less emphasis on case studies. The plurality of related research relates to theory with application (42%). Only 18% are case studies and 8% are based on surveys of practitioners.

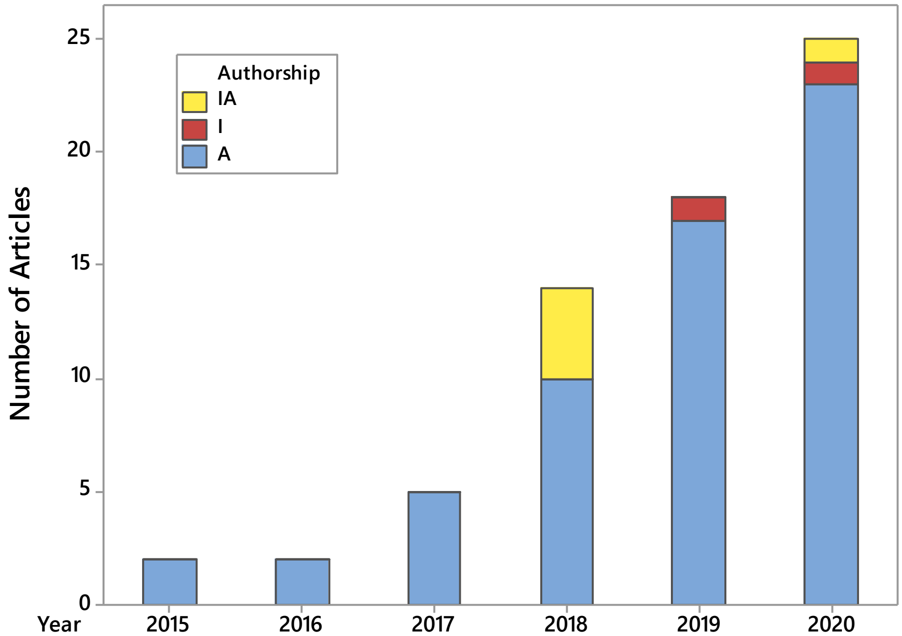

Figure 4 The yearly number of articles and their authorship

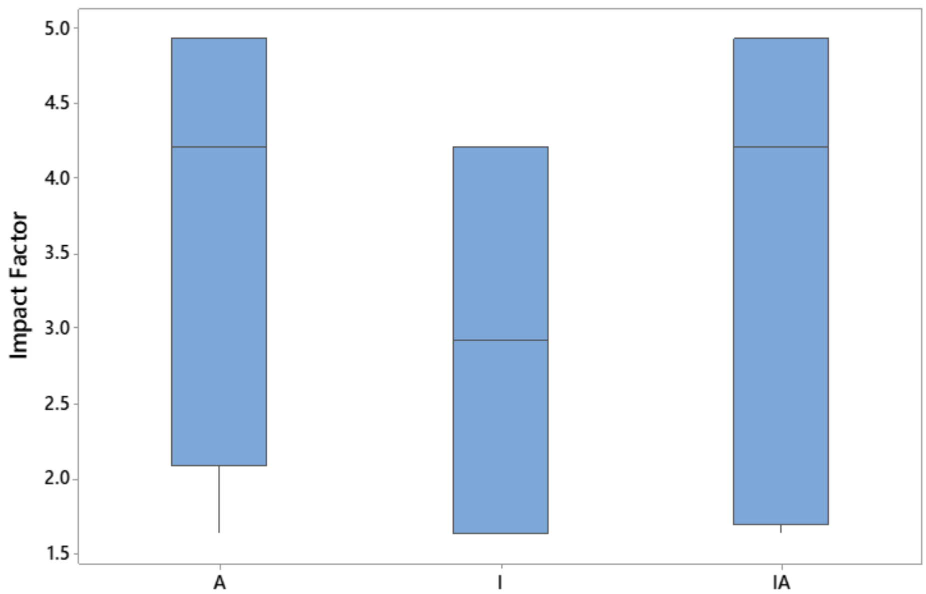

Figure 5 Journal impact factors of articles by industrial sectors

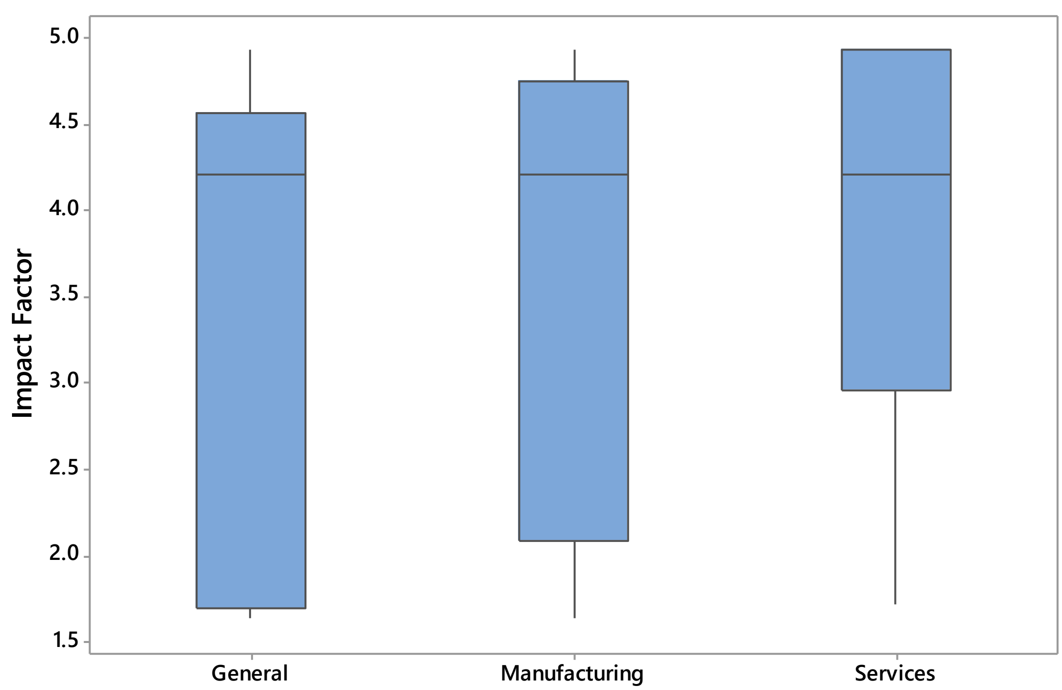

Figure 6 Journal impact factors of articles by industrial sectors

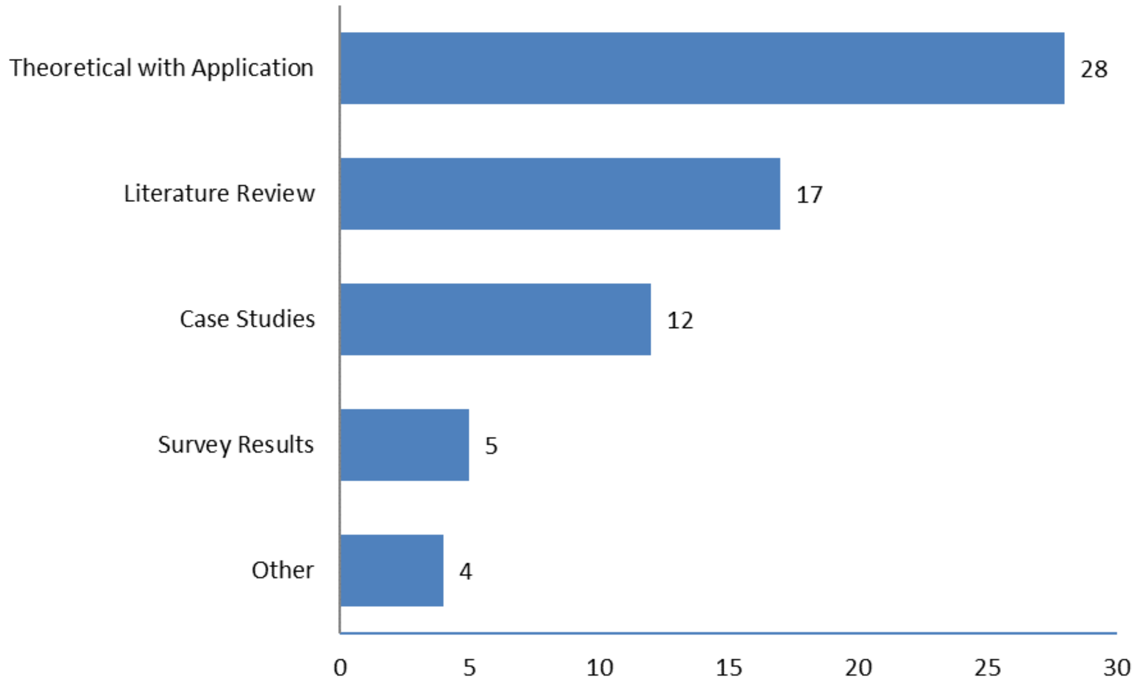

Figure 7 Number of articles by research approach

3.1.3 Topics of Literature

Next, the topics of the articles were examined. Figure 8 shows a pie chart of the percentages on the topics from the general IIOT research summary. The most common topic (42%) of articles relate to operations management. These distinctions indicate the labels that the researchers are using to index their work. Traditional quality-related research might be in the general or safety categories. Therefore, this might suggest that researchers in business schools are the main group currently defining Quality 4.0 research. Engineering topics such as IT-based cloud manufacturing, Cyber-Physical Manufacturing systems, IOT, and computer technologies are studied in the context of more efficient production control[1]. Aside from manufacturing-related topics, publications involve applications in other areas such as supply chain, safety, and ergonomics. This suggests that Quality 4.0 research has the potential to showcase its capability of improving performance through improved efficiency and safety.

Figure 10 bar charts the counts of the most mentioned keywords in the dataset of articles. Industry 4.0 is the most frequently mentioned keyword. Big data and IOT are two trending technologies that show outstanding importance in the framework of future quality engineering. Lean and Six Sigma are relatively rare keyword phrases, indicating the developing transition away from the associated problem-solving methods.

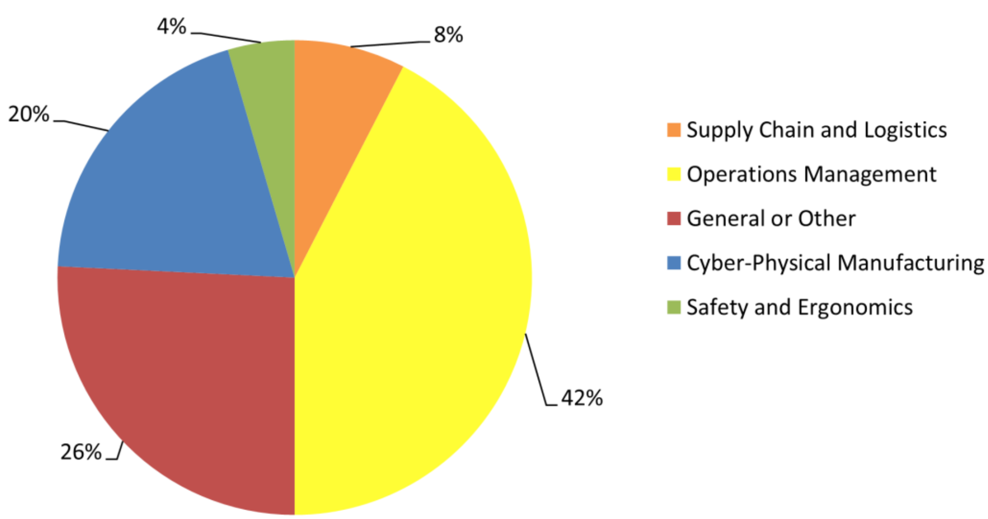

Figure 8 The percentage of articles mentioning IOT manufacturing applications.

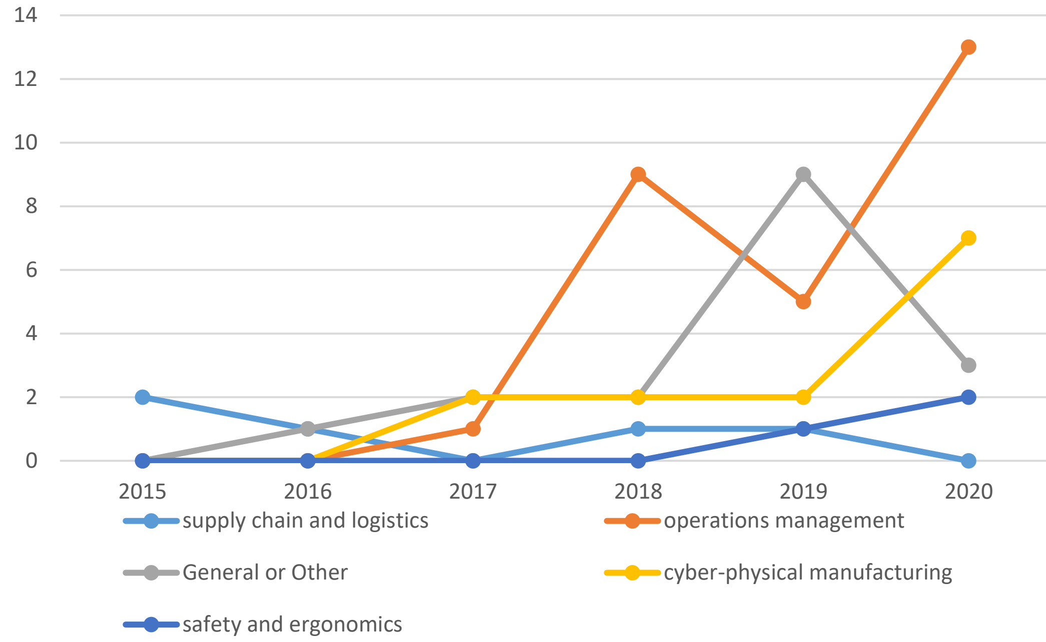

Figure 9 Number of articles in IOT manufacturing applications over time.

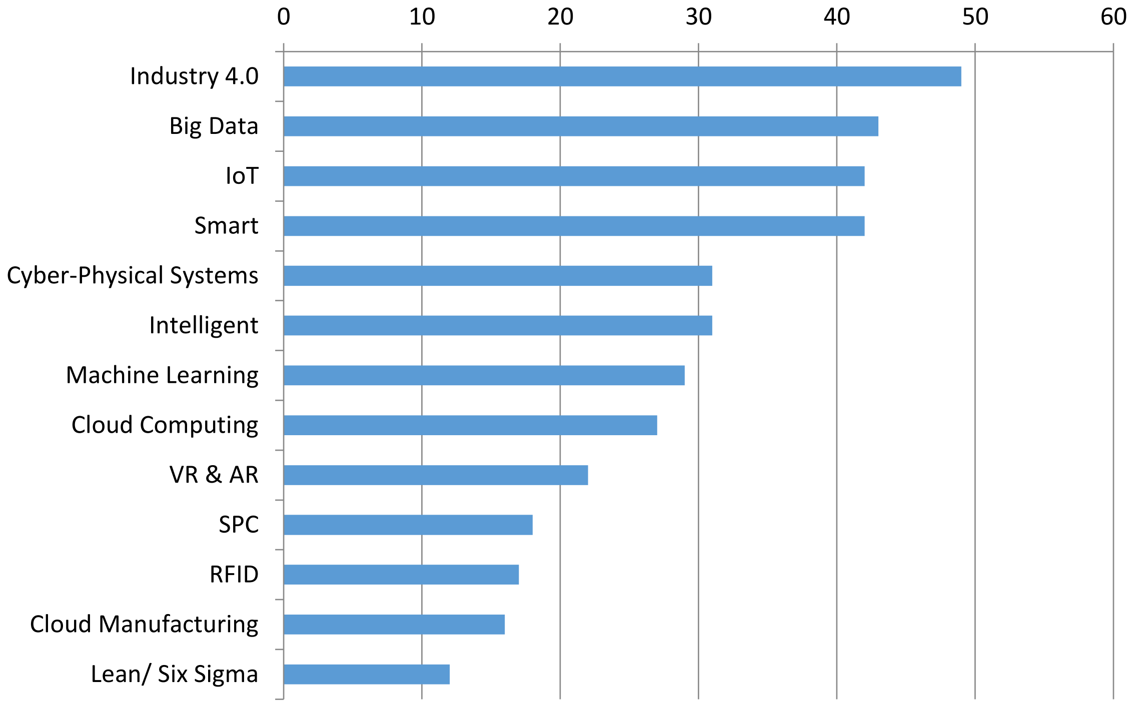

Figure 10 Number of most mentioned keywords

3.2 Research Synthesis

In this section, we review the advances noted by ASQ[3] as having shaped the evolution of Quality 4.0 and its future. This was done by building on the information from the database of Quality 4.0 articles. The ASQ authors summarize and describe four key advance areas:

1. Digitization to permit systems with self-induced corrections,
2. Shifting from Process Operators to Process Designers,
3. Self-regulating and self-managing machines, and
4. Human performance and integration with business objectives.

These areas offer a promising way to categorize and assess the existing articles and inspire new research.

3.2.1 Self-Induced System Corrections

According to ASQ, a big part of the present and future of quality relates to digitization and adaptive learning. Yet, the Quality 4.0 literature contains relatively few entries related to the part of machine learning that allows self-induced system corrections. Some authors have highlighted related needs and provided overviews of related topics. For example, Wuest et al. highlight quality-related challenges for machine learning.[12] They see one machine learning sub-area, Reinforcement Learning (RL), as most relevant to address self-correcting machines.

Reinforcement Learning technology can put in place a control system that takes actions while learning about both the system state and the system parameters. Many RL models can be viewed as applications of the older Partially Observable Markov Decision Processes (POMDP) models. In POMDP, an agent also uncovers the optimal action with the highest rewards while estimating the probabilities that systems are in particular states. The key realization is that the parameters governing the system may be viewed as part of a generalized system- state[13]. Yet, there are little (if any) research about RL specifically targeting quality-related objectives such as variation reduction which could offer an important set of topics for the future.

3.2.2 Shift from Process Operators to Process Designers

Most of the articles reviewed in this study may be judged as intended to support process design. Few articles focus on improving human operator decision-making except as it relates to human-in-the-loop machine learning decision-making. Particularly, many articles offer high technology and mathematical contributions and merely mention Quality 4.0 or IIOT in keywords in passing. This suggests an opportunity for research that explicitly studies human variabilities and translates related information to process designers. For example, if humans are pushing on presses with variable pressures, the process of converting to an automatic system efficiently may serve as a valid Quality 4.0 research topic.

In general, as manufacturing is becoming increasingly digitalized, processes are becoming “smart”. The details of connecting Programmable Logic Controllers and IIOT software systems such as PTC Thingworx, Siemens Mindsphere, and Microsoft Power BI might inspire further research. Such systems are often targeted primarily at monitoring downtime but can support quality improvement activities as well as maintenance and repair.

Also, it seems generally easier to collect big data from systems with high degrees of automation than from manual systems. Also, the variability of automatic systems can generally be expected to be lower than for manual systems. This might cause a need for quality measurements that do not emphasize variability such as uptime. Typically, robotic systems achieve $C_{pk} > 3.0$ while still needing maintenance and monitoring. Research that addresses the ease of obtaining data and/or high levels of traditional quality measures could be of critical interest.

Yet, smart manufacturing generally involves fewer human operators. Therefore, quality improvement is shifting from process operators to process designers, who decide the design of the human-machine interface, data to be collected, and representation. Yet added instrumentation for human operators may also offer important topics for research. For example, process designers can monitor the operator’s state which refers to a variety of psychological, physiological, and cognitive characteristics that may influence a worker’s performance such as motivation, fatigue, emotions, and attentiveness[15].

3.2.3 Self-Management Machines

Industry 4.0 is driving manufacturing enterprises towards network-enabled manufacturing. This involves cyber-physical systems and the connection of manufacturing materials such as sensors, controllers, robots, machines, and products[1]. To make manufacturing systems more efficient and smarter will require that machines be able to predict future events and provide recommendations based on their historical data[14]. As advanced sensing technologies and cloud computing have been adopted to increase information visibility and system controllability, huge amounts of data are going to be generated and collected. Yet, we are not seeing methods in the literature that explicitly target the monitoring of machines that are self-managing. Nor are we seeing explicit quality related research about self-managing machines and related control systems.

Big data analytics also provides efficient and effective methods and tools to handle large-scale production data for information processing and manufacturing process control[1]. In particular, Kulahci et al. studied some common issues with current manufacturing data analytics including (1) Connecting process data with product characteristics; (2) Lack of specialty data resulting from having datasets with little variation after applying Six Sigma and Lean Production. In the literature review, we find some research that might help to solve big data problems. Semi-supervised learning methods can combine the unlabeled product responses with labeled process data to achieve better prediction. Yet, more research is likely needed to fully utilize big data for process monitoring, fault diagnosis, and performance optimization. In addition, big data analyses may require parallelized computing to address computational issues. We have not found much (if any) on the parallel process of data for quality-related objectives.

3.2.4 Human Performance and Integration with Business Objectives

In Industry 4.0, human-computer communication is an important subject [15]. Smart manufacturing necessarily involves the presentation of simulated and real data in an intuitive and trust-building manner[16]. Krugh and Mears (2018) compare Cyber-Human System (CHS) with Cyber-Physical System, which combines people and hardware into the "Internet-of-People-and-Thing" paradigm Intuitively, human intelligence will still be a deciding factor for quality improvement[17]. While there has been significant attention to Quality 4.0 related human-computer interactions, we have seen little (if any) research related to trust of automation and the adversarial nature of cybersecurity in manufacturing quality.

As the quality of products and services continues to be a major factor in business competition, Total Quality Management (TQM) has been implemented by more and more companies to stay competitive. Nardo and Murino (2020) provide insight that typical Industry 4.0 technologies such as Cyber-Physical Systems, Internet of Things, and Big Data can be integrated with the standard Deming cycle to produce quality[18]. Furthermore, a key point of connecting the technologies and the four components of the Deming cycle-

-Plan, Do, Check, and Act--is efficient and effective data representation and visualization. For example, a dynamic Thingworx dashboard that can represent real-time manufacturing data, energy usage, and inventory will facilitate human decision making. Relating IIOT system dashboard design to Quality 4.0 is an important topic for future research.

Chapter 4. Conclusion

In this research, papers relevant to Quality 4.0 that have been published in recent years were reviewed. The literature trends and discuss future research directions for quality engineering in the context of Industry 4.0 were analyzed. The literature on Quality 4.0 is clearly growing, yet there seems to be a dislocation between the vision that Quality organizations have, and the topics published in journals (e.g., of ASQ). In particular, ASQ seems much more aggressive in supporting a change in the nature of quality-related practice than researchers seen interested in providing it. ASQ views a rapid shift to self-machines supported by process engineering and machine learning while many researchers seem to continue with pre-existing topics, only acknowledging the trend with shifting keywords.

In the view of many writers, the field of quality engineering is in crisis. The search phrase “quality engineering” seems to be trending downward and traditional methods such as lean six sigma are garnering reduced interest. This review aims to provide a general map to link works in the area of Quality 4.0 in smart manufacturing. Multiple relatively new topics for research that align with the ASQ published model and predicted evolution were highlighted.

Overall, employing big data and using machine learning promises to change much about both the practice of quality engineering and of related research. An embrace of the real-world systems involved with connecting machines to control centers, creating dashboards, and modeling big data using machine learning systems is particularly critical.

Attention to the decision problems and software systems for Industry 4.0 is also critical. The key software systems for Industry 4.0 or the Industrial Internet of Things include Microsoft's Power BI, PTC's Thingworx, and Siemen's MindSphere.

References

[1] Yang H, Kumara S, Bukkapatnam ST, Tsung F. The internet of things for smart manufacturing: A review. *IISE Transactions*. 2019 Nov 2;51(11):1190-216.

[2] Zonnenshain A, Kenett RS. Quality 4.0—the challenging future of quality engineering. *Quality Engineering*. 2020 Feb 21:1-3.

[3] ASQ https://asq.org/quality-resources/quality-4-0 [1 February 2020]

[4] Radziwill N. Let's get digital. *Quality Progress*. 2018 Oct 1;51(10):24-9.

[5] Watson G. The Ascent of Quality 4.0. *Quality Progress*. 2019 Mar 1;52(3) 24-30.

[6] Moore, M. What is Industry 4.0? Everything you need to know. *TechRadar* 2019.

[7] BMBF-Internetredaktion (21 January 2016). "Zukunftsprojekt Industrie 4.0 - BMBF". Bmbf.de. Retrieved 30 November 2016.

[8] MarketsandMarkets, https://www.prnewswire.com/news-releases/industry-4-0-market-worth-156-6-billion-by-2024--exclusive-report-by-marketsandmarkets-300973105.html [14 September 2020]

[9] Zairi, M. 2017. Deep in crisis: The uncertain future of the quality profession (Quality 4.0). UK: European Centre for Best Practice Management Publishing House.

[10] Zain Z, Dale B, Kehoe D. Total quality management: An examination of the writings from a U.K. perspective. The *TQM Magazine* 2001; 13(2):129–137.

[11] Brady JE, Allen TT. Six Sigma literature: a review and agenda for future research. *Quality and Reliability Engineering International*. 2006 Apr;22(3):335-67.

[12] Wuest T, Weimer D, Irgens C, Thoben KD. Machine learning in manufacturing: advantages, challenges, and applications. *Production & Manufacturing Research*. 2016 Jan 1;4(1):23-45.

[13] Allen TT, Roychowdhury S, Liu E. Reward-based Monte Carlo-Bayesian reinforcement learning for cyber preventive maintenance. *Computers & Industrial Engineering*. 2018 Dec 1;126:578-94.

[14] Frumosu FD, Kulahci M. Big data analytics using semi-supervised learning methods. *Quality and Reliability Engineering International*. 2018 Nov;34(7):1413-23.

[15] Golan M, Cohen Y, Singer G. A framework for operator–workstation interaction in industry 4.0. *International Journal of Production Research*. 2020 Apr 17;58(8):2421-32.

[16] Gorecky D, Schmitt M, Loskyll M, Zühlke D. Human-machine-interaction in the industry 4.0 era. In2014 12th *IEEE International Conference on Industrial Informatics* (INDIN) 2014 Jul 27 (pp. 289-294). IEEE.

[17] Krugh M, Mears L. A complementary cyber-human systems framework for industry 4.0 cyber-physical systems. *Manufacturing letters*. 2018 Jan 1;15:89-92.

[18] Nardo MD, Forino D, Murino T. The evolution of man–machine interaction: the role of human in Industry 4.0 paradigm. *Production & Manufacturing Research*. 2020 Jan 1;8(1):20-34.